The Report Committee for Taylor Yvette Benson's
Certifies that this is the approved version of the following Report:

An Investigation of the Practices Used in Airline Crew Scheduling and Their Impact on the Physical and Mental Health of Airline Crew

APPROVED BY
SUPERVISING COMMITTEE:

Kenneth R. Fleischmann, Supervisor

Jennifer Allen

An Investigation of the Practices Used in Airline Crew Scheduling and Their Impact on the Physical and Mental Health of Airline Crew

by

Taylor Yvette Benson

Report

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Information Studies

The University of Texas at Austin

August 2020

Abstract

An Investigation of the Practices Used in Airline Crew Scheduling and Their Impact on the Physical and Mental Health of Airline Crew

Taylor Yvette Benson, MSIS

The University of Texas at Austin, 2020

Supervisor: Kenneth R. Fleischmann

The literatures surrounding the topics of crew scheduling optimization and crew health are often researched separately. The models are disconnected from the people they affect and are often seen as separate and neutral entities, despite being intrinsically connected with the mental and physical health of flight crews, in the same way that a typical work schedule impacts the physical and mental health of traditional full-time employees. With this in mind, this report gives a high-level overview of popular scheduling models and also, more importantly examines how the use of these models and current schedule optimization practices directly and indirectly impact the health of flight crews.

Table of Contents

Introduction

As industries expand, the reliance on mathematical models and machine learning is becoming more commonplace. Not only can these models work efficiently, they can parse an immense amount of data in a relatively short amount of time. In some industries, the use of this technology is clearly noticeable, such as Amazon using machine learning to present users with recommended products. However, their use in other industries is not as apparent, oftentimes working in the background, serving more as a trickle-down effect. This is especially true for the airline industry.

In 1978, the Airline Deregulation Act was passed. This allowed airlines to set their own fares and select their own routes with minimal interference from the government (Bazargan, 2004). After this, the airline industry began to grow at an exponential rate. The reach of airlines grew, requiring more fleets and crews to be in the air. To keep up with the growth, airlines have employed mathematical models and AI for Crew Resource Management (CRM).

Originally it was thought that, due to airlines being free to compete on price, less vigorous competition on service quality was expected. Since the service competition was lessened, it would lead to a reduction in flight frequencies that were widely viewed as excessive (Brueckner, 2004). However, according to Morrison and Winston, the opposite occurred. A route weighted measure of flight frequency rose by 9.2 percent between 1977 and 1983, generating profits in excess of $10 billion per year (Morrison & Winston, 2010).

Even though the government has limited its scope of control over airlines, that does not mean that regulation does not exist. The International Air Transport Association (IATA) is a trade association that creates and enforces regulations amongst its members consisting of 217 airlines (IATA, 2018). Members of IATA are required to undergo safety and operation audits performed by IATA approved companies. IATA publishes multiple standard guides, including the Standard Schedules Information Manual (SSIM), the Fatigue Management Guide, and the Medical Manual, which give best practices for promoting crew health and enabling safety.

While some of these guides are available freely, many of the guides are sold to members at a high price on top of the dues for annual membership. For larger airlines, the price is negligible, yet there are many small airlines who are also members of IATA, paying a minimum of $13,456 per year in dues (IATA, 2018).

The existence of these guides also does not factor into the algorithms themselves. While there is the possibility of regulation through IATA guides, safety audits, and union involvement on the ground level, the operational algorithms do not factor in the best practices and research. Airlines rely on these algorithms to not only optimize time, but also revenue. These models are specifically built with optimization in mind. However, airlines have to manage thousands of crew members every day. While there are operations experts who do work in scheduling, there was a push to begin automating scheduling processes in the 1990s, a trend that originated in the rail industry (Morgado and Martins, 1993).

There is also the consideration that IATA is a trade association. While they do work in tandem with the FAA, they select and fund the scientists and doctors in charge of drafting these guides and regulations. Not only that, but the FAA judges every airline's safety improvement using a cost-benefit analysis. The Urban Institute calculated the approximate monetary value of a human life at $2.7 million. While this is more than the value of raw materials, rarely does the monetary value of the benefits outweighs the cost to the airline (Roach, 2012).

The literature surrounding the topics of crew scheduling optimization and crew health are often researched separately. The models are disconnected from the people they affect and are often seen as separate neutral entities, despite being intrinsically connected with the mental and physical health of flight crews, in the same way that a typical work schedule impacts the physical and mental health of traditional full-time employees. With this in mind, this report gives a high-level overview of popular scheduling models and also, more importantly examines how the use of these models and current schedule optimization practices directly and indirectly impact the health of flight crews.

This paper is organized as follows: first, we will look at the optimization problem of airline scheduling as a whole and then examine specifically the crew scheduling problem. Next, we will take a high-level overview of prominent algorithms used to solve these optimization problems and also provide descriptions of said algorithms from the literature. Then, we will examine the real-world execution of these solutions through an examination of flight crews. Finally, we will discuss the connection between these two aspects of the airline industry and the responsibility airlines have in overseeing the use of these algorithms and how to ensure a safe environment for passengers and crew.

The Scheduling Process

The top-down process of airline scheduling is robust and complex in its execution. The airline scheduling process is often carried out in a sequential order, so that flight, aircraft, and crew schedules are created in order several months prior to the day of operations. Major U.S. airlines often schedule more than 2500 flights per day. These flights travel to about 150 airports using nearly 500 aircrafts. Considering that all of these aircraft need to be staffed with cockpit and cabin crews, airlines are tasked with scheduling more than 5000 cockpit crews and almost 10,000 flight attendants on a month by month basis. Golpalkrishnan and Johnson (2005) state that, while it is technically easy for the process to be modeled mathematically and seen as an optimization problem, solving that model and producing a practical crew schedule can be exceedingly difficult.

In 2005, the European air transport industry reported that they were suffering from an extreme increase in delays: 42% of flights were delayed and as many as 20% of flights were delayed by more than 15 minutes (Burke et al., 2010). While 19% of delays are due to airport operations, 50% were due to airline related issues (Wu, 2005). Predicted growth in flight transport will cause increased traffic in airports and airspace, which will cause more delays (Lan et al., 2006). These delays, and the increase in air traffic, increased the need for using mathematical models for flight scheduling. The use of these models naturally extends to the scheduling of crew. If implemented, delays propagated by crews and aircraft would be reduced significantly (Dück et al., 2012).

Golparkrishnan and Johnson explain that Airline scheduling consists of five planning stages:

1. **Flight Schedule** This stage involves constructing a schedule consisting of all flights to be flown. Scheduling is typically based on market demands for the flight segments, gathered through market research.

2. **Fleet Assignment** This is the step where available aircrafts are allocated to flight legs. Revenue from a flight leg is dictated by the market for the flight leg and the size of the aircraft used for the leg. The goal is to maximize revenue while working within the constraints that all flight legs must be flown with fleets that are available.

3. **Aircraft Routing** The aircraft routing problem involves the routing of aircraft such that maintenance constraints, like fuel, are satisfied.

4. **Crew Pairings** Also referred to by some as a trip or rotation, crew pairings are the sequence of flight segments that begin and end at a crew base. Each pairing has a cost

associated with it. The objective is to find a subset of these pairings with minimal cost that covers all the flight legs in the schedule exactly.

5. **Crew Rostering** In this stage a monthly schedule that can be flown by the crew is drawn using the optimal set of pairings generated from the previous stage.

This investigation will focus specifically on the crew pairing and the crew rostering phases of scheduling. It is important to note that those stages are restricted to constraints defined by the preceding stages. Crew management, and by extension crew health, is most directly influenced by these later steps.

The Crew Scheduling Problem

As global aviation continues to scale up to more flights among more destinations, the crew scheduling problem becomes increasingly difficult to solve. According to Golpalkrishnan and Johnson (2005) that is due to the following reasons:

First, the number of pairings is extremely large for many airlines. Even with robust legal constrictions, it is not uncommon to create 100 million approved pairings for moderate size fleets and several billions of approved pairings for some of the large North American fleets. The second reason is that many complex work rules and FAA safety regulations have to be satisfied. These are often created after rigorous research from physicians' panels and detailed negotiations with labor unions. Finally, crew costs depend on complex crew pay guarantees and are highly nonlinear.

This is a common observation from the collected literature. AhmadBeygi et al. (2009) describe that the primary objective of airline crew schedulers is to find the most cost-effective assignment of crews, in the cockpit and the cabin, to flights. This process is broken up into two separate processes: pairing and rostering. Crew pairing involves separating flights into pairings, which are multi-day sequences of flights beginning and ending at the crew base that can be flown by a single crew. These pairings are made up of duties, which are one-day work schedules, that are separated with brief periods of rest. This is done for three specific types of flights: the flights that happen every day, the flights that are only flown a few times per week and the flights that serve as transitions between the end of one scheduling period and the start of the next.

Crew pairing includes the process of knowing patterns of flight legs and assigning both the cockpit and cabin crews to these patterns. Currently, total crew costs -- which includes salaries, benefits, and expenses, is the second largest cost for airlines. This is second to the largest expense, fuel costs (Bazargan, 2004). Unlike fuel cost, however, flight crew costs are controllable (Anbil, 1991). From an operations perspective, the use of mathematical models to mitigate costs while also balancing for optimal frequency and flights. These models now directly decide the schedules for members of airline crew, mainly, flight attendants and pilots. While optimization is priority, there are rules that are included as safeguards to ensure crew health. Example of these rules include (Klabjan, 2003):

- Each shift should not exceed 8 hours of flight time
- A maximum length of two days is allowed for a routing (i.e. two-day pairings)
- Establish a home base for the crew being paired
- The minimum and maximum sit time connection times are 10 minutes and 3 hours, respectively

AhmadBeygi et al. (2009) also contributes the complexity of the pairing problem to the non-linear pay scale. Explaining that, the cost of a pairing is the maximum amount of two values: the sum of the costs of individual duties, and a fixed percentage of elapsed time of the pairing, which is known also as time away from base. An individual duty cost is calculated with the maximum of three separate values; the total flying time in the duty, a fixed percentage of the time of the duty, and a minimum confirmed payment per each duty. AhmadBeygi et al. write these equations as such:

$$c_d = \max\{fly_d, \beta e_d, \gamma\},$$

$$c_p = \max\{(\textstyle\sum_d c_d), \alpha T_p\},$$

where

c_d	cost of duty d
fly_d	total flying time of duty d
β	percentage of elapsed time of a duty applied to duty cost function $(0 < \beta < 1)$
e_d	elapsed time of duty d
γ	minimum guaranteed duty payment
c_p	cost of pairing p
α	percentage of elapsed time of a pairing applied to pairing cost function $(0 < \alpha < 1)$
T_p	elapsed time of pairing p

The second step, crew rostering, is when the previously calculated crew pairings are made into longer crew schedules that take the form of rosters or bidlines. Rosters are specific work schedules that are tailored to an individual crew member. Rosters take into account needs, such as training, and preferences, such as desired destination of the assigned flight leg. Bidlines, however, are generic schedules that are assigned to a crew member through a bidding process. Crew members state their preference for different bidlines and then are assigned in decreasing order of seniority, each member getting the unassigned bidline that is ranked highest on their list of preferred schedules. Bidlines are more commonly used in the US while rosters are used in the international markets.

Kohl and Karisch (2004) note that the rostering process adheres to two different rule sets as opposed to a singular set of rules that dictate crew pairing. These are horizontal and vertical rules. Horizontal rules are similar to the rules outlined when solving the crew pairing problem, these rules only affect one roster or bidline. However, vertical rules concern more than just one roster. In most cases, they depend on a subset of rosters, but there are also some that concern the whole schedule. Kohl and Karisch describe that the base regulations of vertical rules consist of: crew complement, qualification-type constraint (which include task and leg qualifications) and global constraints.

Crew complement is assigning the crew into teams that best serve the activities required. Differing activities require different crew complements. Kohl and Karisch (2004) provide an example comparing a short-haul cockpit crew problem, in which flight pairings are usually assigned to one captain and one first officer, and a ground duty such as simulator training that could require two captains and one first officer. They also note that certain tasks may require additional positions like instructors. This often is compared to a qualification-type constraint, which is what complement technically qualifies as, however, due to the importance of this aspect of rostering. It is treated as its own entity.

Qualification-type constraints are tasks that require some crew members to hold some particular qualifications. This tends to mainly affect cabin crew but can also affect cockpit crew. The constraint itself can be applied to a task or flight leg. Examples of qualification-type constraints include limiting the number of inexperienced crew members, crew members that must fly together and language qualifications.

The final Vertical constraint Kohl and Kirsch (2004) define are global constraints. So far, vertical constraints have been specifically applied on all (or some) tasks. Global constraints are constraints, which put requirements on the whole problem solution.

Examples include constraints on bid satisfaction and horizontal rules defined for more than the planning period, such as if a rule is put in place stating that an extra day off must be assigned every quarter of a year.

The factors and considerations for each planned scheduled are immense. Factoring in the fact that this must be done across approximately 15,000 crew schedules. Despite the seemingly strict considerations, there can be millions of legal pairings calculated for each planning period. Crew scheduling is an immense and expensive undertaking, thus succinctly presenting the need for robust algorithms to optimize planning.

Algorithms

The models below are keystone algorithms from each of the different types of programming models used for airline operations scheduling. The intent of this paper is not to give a comprehensive review of the extensive variety of the mathematical models used in the industry, but to provide necessary context for the types of algorithms that are present in the scheduling workflow. This overview is based on Devechi and Demirel (2018), in which they fully examine and provide a survey of airline crew scheduling problems, and proposed solutions from the literature.

Genetic Algorithms

Genetic algorithms were first introduced by Holland (1992) to understand natural processes and population genetics. The primary logic of genetic algorithms attempts to improve a population of candidate solutions by applying a set of genetic operators (crossover and mutation) iteratively and creating new individuals that then replace the old ones.

Levine (1996) describes genetic algorithms (GAs) as search algorithms that are based on an analogy with natural selection and population genetics. GAs are commonly used for finding approximate solutions to difficult optimization problems. Levine dictates the most common airline crew scheduling problem is the set partitioning problem (SPP).

$$\text{Minimize } z = \sum_{j=1}^{n} c_j x_j \tag{1}$$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j = 1 \quad \text{for } i = 1, \ldots, m \tag{2}$$

$$x_j = 0 \text{ or } 1 \qquad \text{for } j = 1, \ldots, n, \tag{3}$$

Where a_{ij} is binary for all i and j, and $c_j > 0$. The objective to determine values for the binary variables x_j that minimize the objective function z. Specifically, in airline crew scheduling, each row (i = 1,..., m) represents a flight leg that must be flown. The columns (j = 1,..., n) represent legal pairings that an airline crew might fly. As previously mentioned, each assignment to a crew comes with a cost, defined by

c_j. The matrix elements a_{ij} are defined by

$$a_{ij} = \begin{cases} 1 & \text{if flight leg } i \text{ is on rotation } j \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Levine notes that the GA model, specifically the steady-state genetic algorithm (SSGA), has weaknesses when tasked with providing feasible solutions. The GA model when compared to traditional operations research methods, consistently underperformed in finding feasible solutions to the SSP. This is because the GA model is intended to be a general-purpose tool. This is what dictated the need for a hybridized model. In which the SSGA works in tandem with a heuristic. Levine presents the newly developed heuristic ROW that takes a row-oriented view of a problem. When working in this hybridized format, the SSGAROW outperformed the two common traditional methods.

According to the literature, genetic algorithms are easy to program and implement and solve small-sized problems effectively without the need for complex commercial mathematical libraries. However, GAs are disadvantaged in terms of quality and performance compared to mathematical based integer problem techniques.

Column Generation

The column generation method is an effective technique created to solve large scale linear problems. The idea is that a large number of linear problems are too massive to consider all the variables explicitly. Most of the variables will be non-basic and assume a value of zero in the ideal solution. This means that only a subset of variables would need to be considered in theory when solving the problem. Devechi and Demirel (2018) state that as the problem grows, the number of columns in the simplex algorithm are able to find millions of variables. This method is based on the idea that it is enough to take only one subset of variables into account while solving the problem. The method divides the problem into a main problem and a sub-problem. The main problem selects the minimum cost among crew pairings in a partitioning or set covering problem. The sub-problem, on the other hand, generates the new crew pairings, or columns, for the main problem.

Zeren (2016), in his development of a column generation model for CRM, iterates that there are many flaws that become apparent from the use of standard column generation. Some of those flaws are slow convergence, also known as the tailing-off effect in which there is a high number of integers required to prove how optimal the algorithm is. There is also the instability in the dual variables that are switching from one extreme point to another, known as the bang-bang effect. Finally, there is the heading-in effect, in which the model produces irrelevant columns; this happens often in early iterations due to poor dual information. Other issues with standard column generation include the plateau effect, which is the degeneracy in the primal and then going forth multiple solutions in the dual information. This leads to the results to remain unchanged for an extended number of iterations (Lübbecke and Desrosiers, 2005). Zeren proposes that to balance with these problems a stabilized column generation implementation is necessary.

Du Merle, Villeneuve, Desrosiers, and Hansen (1999) dictate that the rows represent flight legs to be assigned to crews and the columns represent possible schedules for these crews. That means that it can be formulated as a set partitioning problem. The column generation algorithm is then used to find lower bounds in a branch & bound framework, consisting in a resource constrained shortest path problem. There is some difficulty in obtaining the precise estimates for the optimal values of dual variables, but the possession of a good approximation of the objective function value can be used to calculate an average value for them.

Zeren uses this stabilization method developed by Du Merle, Villeneuve, Desrosiers, and Hansen (1999) but adds new variables and constraints to the two primary equations. The constraints penalize extreme dual variable transformations while remaining within the linear programming framework. While this method overcomes the aforementioned problems, a considerable increase in acceleration and therefore a decrease in the total number of iterations is observed.

Stochastic Crew Scheduling

Devechi and Demirel (2018) explain that traditional airline crew scheduling problems are deterministic and do not involve any potential disruptions. Yet, airlines consistently have to work with irregularities, such as bad weather conditions, carrier delays, late arrivals, or diversion of airline traffic. Stochastic models do take into consideration the impact of unpredictable variables that are associated with air travel, with the goal of using that information to implement thorough solutions that have a better ability to withstand disruptions. The importance of this approach comes from proactively considering the effects of certain scheduling decisions.

Traditional methods consider the airline crew scheduling problem as a deterministic model and do not explicitly incorporate information on potential disruptions. Rather than modelling the crew scheduling problem as deterministic, it deals with a stochastic crew scheduling model. Airline transportation generally has to deal with disruptions, like technical failures or bad weather conditions. Resulting delays force the airline companies to require robust crew scheduling.

Duck et al. (2012) drafted a formula that was a combination of stochastic crew scheduling and aircraft assignment model. This involved them distinguishing two kinds of delays. Firstly, there are primary delays, these delays could not be influenced by the airline operations team e.g. instructions from air traffic control. Then there are reactionary delays. These delays occur due to actions of the airline operations control, such as the instruction to wait for a late aircraft instead of taking another one. Duck et al.'s resulting model includes several nonlinear constraints. The model itself involved the perpetuation of delays through aircraft as well as crew through an integrated recourse function. Duck et al. come to the conclusion that due the propagation model crafted, it is very possible to compute probabilities for disruptions of crew rules as well as occurrence of severe delays. This method served as a way to bridge the gap between traditional operational methods and machine learning principles.

Operational Goals and Consequences

As these methods progress, the goal becomes inherently clear that cost minimization serves as the top priority for airline operations. However, as it is previously stated, the above are not simply scheduling the flights, they are scheduling the crew for these flights as well. There is an understanding that these methods will be actively affecting the work schedule and environment of the cabin crew. In this next section, we will be actively investigating what that exact environment is and how those who have to work under the generated scheduling constraints are affected by them.

Crew Duties

This report focuses on the health profiles of both pilots and flight attendants. While their duties and job requirements vary greatly, their environments, job hours, and occupational hazards are similar. Pilots and flight attendants act as service members for passengers, thus it is necessary to examine how current practices impact both populations.

Bor (2004) explains that pilots' duties involve having the ability to be proficient in navigating complex systems and operations on board aircraft, as well as having the mental and emotional intelligence to be able to work on a team or small crew. Pilots are shift-workers, and as such, their schedules and work routines are vastly different from the modern understanding of the 9-5 work week. Their primary environment consists of a claustrophobic flight deck on board a military or commercial aircraft at an altitude of about 35,000 feet in the air. Bor also states that over the past decade the duties of the modern pilot have changed significantly due to increasing automation on the flight deck. While traditional piloting and navigation skills are still necessary, especially in emergency situations, there is now a much greater emphasis on operational tasks, communications, and computer programming. When operating as part of a crew, a pilot's actions are subjected to intense scrutiny from other crew members, which can oftentimes serve as an axis of mental strain. Regular simulator and line tests, as well as medical assessments for physical and psychological fitness are also required of pilots.

The literature regarding flight crew health is relatively minimal and of varying quality, especially in the case of flight attendants. Frequently, the research tends to focus specifically on pilots which is an understandable focus, as the assumption is that the pilot's health coincides directly with the safety of the passengers. Flight attendants have a similar work environment, having to engage in an intense amount of physical labor. There is also an understated emotional and mental component, similar to those who work in food service and retail. Lee (2015) explains that flight attendants employ emotional labor strategies such as surface acting and deep acting when they confront a situation that requires emotional labor. Surface acting calls for expressing certain emotions expected of them in the workplace, while deep acting means expressing the actual emotions mandated by the employer, as in the expression of insincere emotional responses as opposed to the expression of genuine emotional responses. This leads to emotional dissonance, which is not ideal in the service industry.

Flight attendants are typically in flight 50–80 h per month, and their maximal flight hours range from 75 to 105 h per month (AFA 2001). Even though flight attendants are perceived to be solely service workers, those who work in those positions would say that is definitely not the case. According to Delta (2017), flight attendants only dedicate one day of their ten-week training to food and beverage service, a majority of their training is spent learning evacuation protocols and first-aid response. An AFA-CWA report by Kolander (2005) explains that responsibilities of flight attendants require them to be on board to assist in case an aircraft emergency evacuation is necessary as well as acting as inflight first responders who are trained to handle smoke and fire incidents, and medical emergencies including CPR and emergency births. Not only that but, since the terrorist attacks of September 11, 2001, flight attendants have assumed increased responsibilities for protecting the safety and security of air travelers against targeted attacks during flight. It has become even more important for flight attendants to be constantly vigilant of the situation in the aircraft cabin, notice and monitor unusual passenger behavior, and be aware of their surroundings at all times.

Crew Health Profile

While scheduling algorithms are regulated in ways similar to the one iterated above, they were still written in an industry where optimization is the key priority. Do these rules and regulations provide sufficient safeguards in regard to crew health? Specifically, what bearing does crew health have on flight operations? One can assume that these occupations with unorthodox scheduling practices and a focus on physical labor in uncomfortable environments do come with a few occupational hazards. Yet, when those who are experiencing these hazards when their jobs involve maintaining passenger aircraft, these hazards can have deadly consequences. Research into airline pathology states that an immense majority of plane crashes occur on takeoff or landing, either on or near the ground. According to the research collected by Roach (2012), 80 to 85 percent of plane crashes are potentially survivable. The emphasis is being placed on the phrase potentially, the implication being that if everything adheres to the projected ideal outcome in the FAA-required cabin evacuation simulation, there is a high possibility that passengers on said flight will survive the crash. While federal regulations require airplane manufacturers to construct their aircraft in a way that enables the evacuation of passengers through half of a plane’s emergency exits within ninety seconds, this is often not the case. These highly survivable crashes tend to end in high fatality rates. Roach's investigation reveals that if you look at survivable crashes, it is rare that half of the emergency exits open. However, there is also the case of confusion, evacuating over one hundred people in an intense emergency situation even with intense training, is quite difficult. It requires coordination and an understanding of the environment. The main point is, passenger survival in emergencies is intrinsically tied to the training and ability of flight attendants. So, one could make the argument that it is in the best interest of the airline that the health of their flight attendants should be a top priority, however, according to the literature, this is not the case.

According to collected ethnographic data, we cannot assert that current safeguards are sufficient. Pilots and flight attendants experience high levels of burnout on a consistent basis. According to Fanjoy (2010) Burnout is defined as "a prolonged response to chronic emotional and interpersonal stressors on the job" (p.17). Fanjoy explains that a lot of the work that cabin crews engage in perpetuates long periods of burnout. Firstly, crews generally have no space for workplace growth or autonomy. Considering that the primary duty of flight crews is to conduct routine flight services. These routines are tedious, frequently lacking challenge, complicity, and autonomy (Liang & Hsieh, 2005). If there is the perception that one's job is lacking challenge and autonomy, their commitment to objectives and efforts have a potential to be affected in a negative fashion. Not only that, but a job lacking feedback could directly adjust the psychological response of success, which can greatly affect a person's work attitude.

Pilot burnout is a contributing factor in accidents and incidents in regional airline operation. Not only that, but due to the perpetuation of a culture built on optimization, pilots feel pressured to meet on-time goals (Fanjoy, 2010).

We also have to examine health concerns in working long aircraft hours in general. Crew shift hours, as they are currently enacted, are shown to increase the risk of impaired cognitive function, adverse cardiovascular effects and adverse gastrointestinal effects (Cahill et al., 2018).

There is also the case of fatigue. One of the consistent occupational hazards that occurs with work in air travel is jet lag. While it is perceived to be a simple term from the result of exhaustion that comes with an immediate time zone shift, jet lag, in actuality is composed of a multitude of symptoms, including daytime fatigue, impaired alertness, insomnia, loss of appetite, reduced cognitive skills, and depressed mood. There is also a variance in severity of said symptoms that is dependent on the number of time zones crossed, as well as the direction of travel. Eastbound travel impacts one's ability in falling asleep, whereas westbound travel interferes with sleep maintenance, which is one's ability to stay asleep (Srinivasan et al., 2017). Once again referring to Kolander's report, she writes that her team had reports from flight attendants admitting that due to fatigue they had forgotten to arm their evacuation slides, or due to fatigue had forgotten they had unaccompanied minors onboard and allowed them to leave the aircraft by themselves. She goes on to say that due to fatigue, flight attendants have fallen asleep or nearly fallen asleep on their jumpseats during landing. The same jumpseats that are located next to the emergency exit doors which would need to be used in the event of an emergency evacuation. Which, as an isolated incident seems negligible, but if we remember that most plane crashes occur during takeoff and landing, this is quite alarming. Kolander's report also goes on to explain how this affects crew outside of the airport bringing up examples from flight attendants that have said they are too fatigued to drive home, or operate their car, for fear of getting into an accident. She even presents evidence of reports of crew being stopped by law enforcement when driving due to the fact that police believed they were driving under the influence of alcohol because of reckless driving. This is alarming because prior to that they would have, by the FAA's account at the time, been okay to operate the emergency equipment onboard an aircraft in a fatigued fashion

Long hours in aircraft leading to physical complications is not surprising when we consider the exact construction of an aircraft. Airplanes are sealed, pressurized cabins that use recycled air. Air quality is actually an underrecognized occupational hazard that is considered when discussing quality of life working on an aircraft. While there has been a significant reduction in cabin environment toxicological risks to flight attendants since the elimination of smoking on board aircraft, there are still intermittent concerns about air quality, including some fume and odor incidents, such as offgassing from upholstery (Griffiths, 2012). It is difficult to justify changing the overall construction of the aircraft. The sealed nature is necessary for ensuring protections during travel. Ambient conditions outside the plane include very cold temperatures, extremely dry air, too low a level of oxygen at partial pressure to sustain life, erratic spikes of high ozone, pockets of air turbulence and levels of cosmic radiation approximately 100 times higher at normal cruise altitudes than it is at ground level. With that being said, the environment inside the aircraft cabin must be clean, safe and comfortable for passengers and crew while also working within the constraint of the airplane's construction (Crump, 2016). The aircraft cabin is similar to other indoor environments, such as homes and offices, in that people are exposed to a mixture of outside and recirculated air, the outside air is generally provided by a compressor on the engine. Yet, the cabin environment is different in many aspects—for example, there is a high occupant density that comes with the current nature of passenger aircraft, the passengers are also unable to leave at will, and finally there is the need for pressurization. In flight, people encounter a combination of environmental factors that includes low humidity, low air pressure, and sometimes exposure to air contaminants, such as ozone carbon monoxide (CO), various organic chemicals, and biological microbia (National Research Council, 2002). It would not be undue for us to compare aircraft to what are commonly known as sick buildings. Sick buildings, in short, are airtight enveloped buildings that have poor air circulation. They become "sick" due to the poor air circulation not allowing indoor air pollutants to be ventilated out of the building. Passenger cabins of aircraft are among the most rigorously defined volumes of air space constantly occupied by humans. Not only that, but aircraft passengers and crew are placed into a closely packed situation for long periods of time with a small provision of fresh air (Hocking, 1998). One can argue that due to their similarities, passenger aircraft can also fall victim to sick building syndrome.

Symptoms of sick building syndrome include: mucous-membrane irritation, neurotoxic effects, respiratory symptoms, skin symptoms and chemosensory changes (Redlich et al., 1997). These symptoms correspond with the reported symptoms of those who work for long periods of time in aircraft. Aircraft air quality is a persistent problem and a catalyst for health issues amongst cabin crew (Boyd & Bain, 1998). While mortality from diseases, like cancer are on a decline amongst cabin crew populations (Hammer et al., 2014). Bronchitis is three times more prevalent amongst flight attendants than the general population (McNeely et al., 2014).

What seems to be clear is that at the surface level, airline scheduling models account for labor regulations and requirements, these are not accounting for prolonged environment exposure and fatigue. The models are built on what is considered to be a mitigation for overexertion, however these considerations do not happen in a vacuum. Twelve to 14 hour shifts may not seem excessive on paper, but the conditions in which those hours are spent can drastically affect the physical and mental health of those working in those environments.

Regulations at the Ground Level

It is not as if there are zero protocols ensuring the safety of airline cabin crews. According to the Association of Flight Attendants – CWA (AFA-CWA, 2013) in 1996, the FAA released a statement that acknowledged that fatigue has the possibility to negatively affect flight attendant performance. As a response they implemented the Flight Attendant Duty and Rest requirements. Originally the regulation required a minimum of 9 hours, which can be reduced to 8 hours if the following rest period is 10 hours. There is also a discrepancy between the regulations of flight attendant fatigue mitigation and pilot fatigue mitigation. In a testimony from Friend (2007) she states that oftentimes, flight attendant fatigue has many of the same issues contributing to it as pilot fatigue. A primary issue is the scheduled length of a continuous period of being awake. Flight attendants are even more susceptible in this area because, unlike pilots, they do not have an actual hard limit on flying time in a 24-hour period. The timing of work hours, time zone shifts, and any subsequent impact of off-duty sleep quality contribute to flight attendant fatigue and in fact may pose a greater risk to flight attendants.

However, those at the AFA-CWA argued that since the proposed included the time that involves exiting the airport, acquiring and taking local transportation to a rest facility—such as hotel or crew lodging—and then transportation back to the airport for the next duty day, it seemed at that point the proposed rest requirement seems inefficient. The FAA agreed, and in 2018 they upped the mandatory rest hours between domestic duties to be an unchanging 10 hours.

While having said to consumers that crews are well trained and incentivize prioritizing safety, when making decisions regarding flight operations, it appears that subtle company pressures associated with retaining continued employment frequently override common sense decision making that is intrinsic to the position of being an industry crew member (Fanjoy, 2010).

Algorithms for Change

While little work has been done to date on the adjustment of current algorithms to account for exposure to hazardous conditions in aircraft, the full impact of fatigue, especially on those in aviation, is often understated, but many of its effects have long been known. As previously stated, flight crews are assigned duty periods that often stretch beyond 10 or 12 hours. These work periods call for nighttime alertness, and layovers in new time zones that force flight crews into unorthodox and unideal sleep schedules.

Although traditional models account for the ground level restrictions put in place by the government, judging by the increasing focus on fatigue-related safety, it is clear that the current rules do not sufficiently account for fatigue's effects on cabin crew and by extension passenger safety. We understand that the current policies of limiting crew fatigue through hard regulations accounts for fatigue indirectly mitigate crew fatigue, when so much of the crew scheduling problem is built through mathematic models, not modeling crew fatigue leads to a system that underserves the needs of the flight crew. There is a current assumption that fatigue is a function of duty and that it is an unavoidable consequence of air travel that cannot be accurately calculated. However, there is literature that shows that may not be the case.

Yidtz et al. (2017) proposes an approach that provides a mechanism to measure fatigue at the pairing level. The goal being to model fatigue explicitly and incorporate it in crew pairing optimization. The model that captures the trade-off between operating costs and fatigue levels by explicitly accounting for fatigue in the objective function.

They use the Three Process Model of Alertness as a method to quantify crew fatigue and alertness in a realistic manner. This model, as initially presented by Åkerstedt and Folkard (1990), factors in two body processes: the homeostatic and the circadian. The homeostatic body process, calculates the alertness lost while a person is awake, and the alertness regained during sleep while the circadian process presents the effect of sleep cycles on alertness.

Yidtz et al. (2017) then built a model off of the previously mentioned column generation algorithm where the subproblem is a shortest path problem with fatigue that is solved using a label setting algorithm. Yidtz et al. (2017) tested three fatigue-based objectives. They then carried out a detailed numerical analysis and testing based on two industry data sets. Their results revealed the substantial effect of accounting for fatigue explicitly on the optimal pairings; and that notable decreases. Their proposed model proves that it is possible to calculate the fatigue associated with each possible crew pairing. This method, if implemented, can provide optimal safeguards at the solution level.

Conclusion

In the collection of the above research, we can come to the conclusion that we have the technological capability to create a holistic and thorough solution to the crew scheduling problem. What we can see is that the research is treating these problems as two separate issues. There is a dissonance between the crew scheduling problem and the crew health problem, however these things are inherently connected. How the crew and pilots are scheduled directly impacts their health. Scheduling decides what time zones are crossed, frequency of flights, and crew exposure to unhealthy cabin conditions. There are aspects of the crew health problem that are seemingly unavoidable and are symptomatic of the environment of the airplane itself. Yet, the fact that a majority of these scheduling techniques do not consider that exposure and these outcomes is an extreme oversight. Especially when we consider that certain decisions made can have fatal consequences. The necessary takeaway is that all of the literature surrounding these topics present them as separate issues, not mentioning how the choices made in the development of the algorithm can affect outcomes at the consumer facing level. It would be irresponsible to suggest that we eliminate the use of mathematic models in the context of scheduling, due to the fact that the airline industry requires robust and efficient management beyond traditional methods, however it is clear that these algorithms in use are not perfect and need to be adjusted. Not only that, but we should be working towards a synergy between development of scheduling algorithms and traditional operations-based management processes.

What is also clear is the fact that, it is not only morally justifiable but economically justifiable that we ensure the health and safety of cabin crew. An error caused due to cabin crew exhaustion can lead to a tragic loss of life in the event of an inflight emergency or during an evacuation. While certain mistakes, generally those on the flight attendant level, are often not obvious because of the low probability of accidents occurring, there still exists for a potentially fatal mistake. Even if we were to ignore the context of the potential for extremely devastating loss due to the physical and mental conditions of flight crews, it is still our moral duty to ensure a healthy environment for service workers. There is also the duty of the airlines, the relationship between the FAA, the IATA, and the airlines they regulate have a symbiotic relationship, the FAA tends to create their regulations with the optimization of airlines in mind (Roach, 2012). History has shown that the airline industry has been reluctant to instate progressive action towards ensuring the health and safety of their crews (Kolander, 2005). Often if the algorithms are calibrated solely with their operational needs in mind, the health of the worker tends to be low priority. Which is why it is imperative that not only we implement more constraints when developing these models, but also to encourage airlines to ensure the safety of their crews through progressive policy.

In the future I would like to use this research as the base for an ethnographic field study investigating the firsthand connection between cabin crew health and the information technology surrounding airline operations management on a wider scale. While this paper focused specifically on mathematic models, I would like to further investigate other technological aspects that impact physical and mental health, such as galley managers and communication interfaces. I would also like to take the time to extend this research past cabin crew, as information technology affects all personnel that works within the airline industry and their performance can also impact the safety of passengers and crew.

References

AhmadBeygi, S., Cohn, A., & Weir, M. (2009). An integer programming approach to generating airline crew pairings. *Computers & Operations Research*, *36*(4), 1284-1298. https://doi.org/10.1016/j.cor.2008.02.001

Anbil, R., Gelman, E., Patty, B., & Tanga, R. (1991). Recent advances in crew-pairing optimization at American Airlines. *Interfaces*, *21*(1), 62-74.

Akerstedt, T., & Folkard, S. (1990). A model of human sleepiness. *Sleep*, *90*, 310-313.

Association of Flight Attendants (AFA). (2001). Information on flight attendant demographics. Memo from C. Witkowski, Director of Safety and Health, Association of Flight Attendants, Washington, DC, to Eileen Abt, National Research Council.

Bayliss, C., De Maere, G., Atkin, J. A. D., & Paelinck, M. (2017). A simulation scenario based mixed integer programming approach to airline reserve crew scheduling under uncertainty. *Annals of Operations Research*, *252*(2), 335–363. http://dx.doi.org.ezproxy.lib.utexas.edu/10.1007/s10479-016-2174-8

Bazargan, M. (2016). *Airline operations and scheduling*. Abingdon, UK: Florence: Taylor and Francis.

Bennett, S. A. (2006). A longitudinal ethnographic study of aircrews' lived experience of flying operations at a low-cost airline. *Risk Management*, *8*(2), 92-117. doi:10.1057/palgrave.rm.8250009

Bennett, S. A. (2017). Aviation's normal operations safety audit: A safety management and educational tool for health care? Results of a small-scale trial. *Risk Management and Healthcare Policy*, 10, 147. doi:10.2147/RMHP.S131763

Bor, R. (2018). *Anxiety at 35,000 feet: An introduction to clinical aerospace psychology*. Abingdon, UK: Routledge. https://doi.org/10.4324/9780429471872

Boyd, C., & Bain, P. (1998). 'Once I get you up there, where the air is rarified': Health, safety and the working conditions of airline cabin crews. *New Technology, Work and Employment, 13*(1), 16-28. doi:10.1111/1468-005X.00035

Brueckner, J. K. (2004). Network structure and airline scheduling. *The Journal of Industrial Economics*, *52*(2), 291-312. doi:10.1111/j.0022-1821.2004.00227.x

Burke, E. K., De Causmaecker, P., De Maere, G., Mulder, J., Paelinck, M., & Vanden Berghe, G. (2010). A multi-objective approach for robust airline scheduling. *Computers and Operations Research*, *37*(5), 822-832. doi:10.1016/j.cor.2009.03.026

Cahill, J., Cullen, P., & Gaynor, K. (2018). Estimating the impact of work-related stress on pilot wellbeing and flight safety. *In H-Workload 2018: 2nd International Symposium on Human Mental Workload: Models and Applications* (p. 7).

Caldwell, J. A. (2005). Fatigue in aviation. *Travel Medicine and Infectious Disease*, *3*(2), 85–96. https://doi.org/10.1016/j.tmaid.2004.07.008

Crump, D. (2016). Air quality in aircraft: A continuing debate. *Indoor and Built Environment*, *25*(5), 725–727. https://doi.org/10.1177/1420326X16654756

Delta Airlines. (2017). *Earning Our Wings: Episode 6—YouTube*. https://www.youtube.com/watch?v=KddtjFY75Go&list=PLwcGJbNwoJpdA4ZlKSs_ZzHZzLkQS2cMH&index=6

Deveci, M., & Demirel, N. Ç. (2018). A survey of the literature on airline crew scheduling. *Engineering Applications of Artificial Intelligence*, *74*, 54–69. https://doi.org/10.1016/j.engappai.2018.05.008

Dück, V., Ionescu, L., Kliewer, N., & Suhl, L. (2012). Increasing stability of crew and aircraft schedules. *Transportation Research Part C: Emerging Technologies*, *20*(1), 47–61. https://doi.org/10.1016/j.trc.2011.02.009

du Merle, O., Villeneuve, D., Desrosiers, J., & Hansen, P. (1999). Stabilized column generation. *Discrete Mathematics*, *194*(1), 229–237. https://doi.org/10.1016/S0012-365X(98)00213-1

Fanjoy, R. O., Harriman, S. L., & DeMik, R. J. (2010). Individual and environmental predictors of burnout among regional airline pilots*. International Journal of Applied Aviation Studies*, *10*(1), 15-30.

Gopalakrishnan, B., & Johnson, E. L. (2005). Airline crew scheduling: State-of-the-art. *Annals of Operations Research*, *140*(1), 305-337.

Gupta, S., Khare, M., & Goyal, R. (2007). Sick building syndrome—A case study in a multistory centrally air-conditioned building in the Delhi City. *Building and Environment*, *42*(8), 2797–2809. https://doi.org/10.1016/j.buildenv.2006.10.013

Griffiths, R. F., & Powell, D. M. C. (2012). The occupational health and safety of flight attendants. *Aviation, Space, and Environmental Medicine*, *83*(5), 514–521. https://doi.org/10.3357/ASEM.3186.2012

Hammer, G. P., Auvinen, A., De Stavola, B. L., Grajewski, B., Gundestrup, M., Haldorsen, T., Blettner, M. (2014). Mortality from cancer and other causes in commercial airline crews: A joint analysis of cohorts from 10 countries. *Occupational and Environmental Medicine*, *71*(5), 313-322. doi:10.1136/oemed-2013-101395

Hocking, M. B. (1998). Indoor air quality: Recommendations relevant to aircraft passenger cabins. *American Industrial Hygiene Association Journal*, *59*(7), 446–454. https://doi.org/10.1080/15428119891010181

Holland, J. H. (1992). *Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence*. Cambridge, MA: MIT press.

IATA. (2018). *IATA's industry priorities*. Retrieved from https://www.iata.org/about/pages/priorities.aspx.

Klabjan, D. (2003). Large-scale models in the airline industry. *Dept. of Mechanical and Industrial Engr., University of Illinois, Urbana-Champaign, IL*.

Kohl, N., & Karisch, S. E. (2004). Airline crew rostering: Problem types, modeling, and optimization. *Annals of Operations Research*, *127*, 223–257. https://doi.org/10.1023/b:anor.0000019091.54417.ca

Kolander, C. K. (2005). Fatigue: The flight attendant perspective. *Association of Flight Attendants-CWA,*1-9.

Friend, P. (2007) Testimony Of Patricia A. Friend International President Association Of Flight Attendants – CWA, AFLl-CIO Before The Subcommittee On Aviation Of The Transportation And Infrastructure Committee. *US House of Representatives, Washington D.C.,* 1-5

Lan, S., Clarke, J. P., & Barnhart, C. (2006). Planning for robust airline operations: Optimizing aircraft routings and flight departure times to minimize passenger disruptions. *Transportation Science*, *40*(1), 15-28.

Lee, C., An, M., & Noh, Y. (2015). The effects of emotional display rules on flight attendants' emotional labor strategy, job burnout and performance. *Service Business*, *9*(3), 409–425. https://doi.org/10.1007/s11628-014-0231-4

Levine, D. (1996). Application of a hybrid genetic algorithm to airline crew scheduling. *Computers & Operations Research*, *23*(6), 547–558. https://doi.org/10.1016/0305-0548(95)00060-7

Longo, L., & Leva, C. (n.d.). *H-Workload 2018: 2nd International Symposium on Human Mental Workload: Models and Applications*. 237.

Lübbecke, M., & Desrosiers, J. (2005). Selected topics in column generation. *Operations Research*, *53*, 1007-1023. https://doi.org/10.1287/opre.1050.0234

Mcneely, E., Gale, S., Tager, I., Kincl, L., Bradley, J., Coull, B., & Hecker, S. (2014). The self-reported health of U.S. flight attendants compared to the general population. *Environmental Health*, *13*(1). doi: 10.1186/1476-069x-13-13

Morgado, E. M., & Martins, J. P. (1993). An AI-based approach to crew scheduling. *Proceedings of 9th IEEE Conference on Artificial Intelligence for Applications*, 71–77. https://doi.org/10.1109/CAIA.1993.366659

Morrison, S., & Winston, C. (2010). *The evolution of the airline industry*. Washington, DC: Brookings Institution Press.

National Research Council. (2002). *"The Airliner Cabin Environment and the Health of Passengers and Crew"* Washington, DC: National Academy Press https://doi.org/10.17226/10238

Redlich, C. A., Sparer, J., & Cullen, M. R. (1997). Sick-building syndrome. *The Lancet*, *349*(9057), 1013-1016.

Roach, M. (2012). *Stiff: The curious lives of human cadavers*. London: Penguin.

Srinivasan, V., Singh, J., Pandi-Perumal, S. R., Brown, G. M., Spence, D. W., & Cardinali, D. P. (2010). Jet lag, circadian rhythm sleep disturbances, and depression: The role of melatonin and its analogs. *Advances in Therapy*, *27*(11), 796–813. https://doi.org/10.1007/s12325-010-0065-y

Su-Chiun Liang, & An-Tien Hsieh. (2005). Individual's Perception of Career Development and Job Burnout Among Flight Attendants in Taiwan. *International Journal of Aviation Psychology*, *15*(2), 119–134. https://doi.org/10.1207/s15327108ijap1502_1

Wang, J., Keil, M., Oh, L.-B., & Shen, Y. (2017). *Impacts of organizational commitment, interpersonal closeness, and Confucian ethics on willingness to report bad news in software projects*. *Journal of Systems and Software*, *125*, 220–233. doi: 10.1016/j.jss.2016.12.004

Wu, C. L. (2005). Inherent delays and operational reliability of airline schedules. *Journal of Air Transport Management*, *11*(4), 273-282.

Yildiz, B. C., Gzara, F., & Elhedhli, S. (2017). Airline crew pairing with fatigue: Modeling and analysis. *Transportation Research Part C: Emerging Technologies*, *74*, 99–112. https://doi.org/10.1016/j.trc.2016.11.002

Zeren, B., & Özkol, I. (2016). A novel column generation strategy for large scale airline crew pairing problems. *Expert Systems with Applications*, *55*, 133–144. https://doi.org/10.1016/j.eswa.2016.01.045